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Downloading Wisdom from Online Crowds

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ABSTRACT

Downloading Wisdom from Online Crowds*

The internet and other large textual databases contain billions of documents: is there useful information in the number of documents written about different topics? We propose, based on the premise that the occurrence of a phenomenon increases the likelihood that people write about it, that the relative frequency of documents discussing a phenomenon can be used to proxy for the corresponding occurrence-frequency. After establishing the conditions under which such proxying is likely to be successful, we construct proxies for a number of demographic variables in the US and for corruption across countries and US states and cities, obtaining average correlations with occurrence-frequencies of 0.47 and 0.61 respectively. We also replicate results from two separate published papers establishing the correlates of corruption at both the state and country level. Finally, we construct the first index of corruption in US cities and study its correlates.

JEL Classification: J11, C81, B40

Keywords: internet, textual databases, document-frequency, proxy variables

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1. Introduction

When judgments made by large numbers of people are aggregated into a single estimate, be it through sophisticated prediction markets (Justin Wolfers and Eric Zitzewitz, 2004) or by simply averaging judgments of experts or even uninformed respondents (Robert T. Clemen, 1989), the result is often remarkably accurate, a regularity popularized as *The Wisdom of Crowds* in the homonymous book.[1]

In this paper we are interested in the possible "wisdom" resulting from the aggregation of a very specific kind of judgment, namely, the determination of which topic is worth writing about. Assuming that, all else constant, the more often a phenomenon occurs the more likely somebody is to write about it, aggregate measures of what large numbers of people write about, *document-frequency,* should be correlated with the relative frequency with which the discussed phenomena have occurred, *occurrence-frequency*. Here we examine the potential for such correlation to be exploited to proxy for the occurrence-frequency of difficult-to-observe phenomena.

Of course, we do not expect document-frequency to be correlated with occurrence-frequency in all circumstances. We do believe, however, that it is possible to judge ex-ante whether such an association is likely. We therefore devise a conceptual framework to derive several specific data-checks to assess if a given document-frequency is likely to be a valid proxy. The data-checks provide necessary conditions for document-frequencies in large, decentralized textual databases to be correlated with their counterpart occurrence frequencies.

We operationalize the estimation of document-frequencies by conducting both internet (via the search engine *Exalead*®) and newspaper (via the newspaper data-bank

[1] Surowiecki (2004) "*The Wisdom of Crowds*", Doubleday, New York.

Newsbank®) searches for documents containing the keyword describing the phenomenon of interest in proximity (within 16 words) of the name of the location of interest. The resulting number of documents is deflated by the total number of documents containing the keyword for the location of interest.[2]

For instance, on April of 2008 the internet search-engine Exalead® had indexed 1,551 web documents with the word "corruption" in proximity to "Sweden" out of the nearly 19 million with "Sweden" in them. For "Russia" in contrast, a keyword identifying an unambiguously more corrupt country, these figures were 12,495 and 26 millions respectively. Relative document-frequency about corruption, therefore, correctly identifies Russia as the more corrupt country. This is not an anomalous achievement. The document-frequency based corruption index we construct, for 156 countries, is correlated .62 with that of Transparency International (TI), the leading international indicator of corruption. Figure 1 illustrates the strong association between these two (log-standardized) variables.

*** Figure 1 ***

We use this technique to assess the ability of document-frequency to proxy for occurrence-frequency by constructing proxies for a set of salient economic and demographic variables whose true value is readily observable (population's racial composition and share foreign-born, and poverty and murder rates) for both states and cities in the United States. We obtain strongly significant correlations with occurrence-

[2] Note that an advantage of using document-frequencies, as opposed to locally-generated data proxies (e.g. local perception surveys), is that we also capture outsiders' perceptions about the frequency of a phenomenon relative to other locations. This is a useful property because the perceptions of locals living in the area of interested could be mediated by characteristics that we may want to correlate with the document-frequency proxy.

frequencies: an average correlation of .56 for state-level variables and of .38 for city-level ones.

Subsequently, we test the usefulness of this technique in a more natural application: proxying for variables that are not easily observable. We focus on corruption because it is a difficult-to-measure variable, of interest to economics, and whose variation can be analyzed at different levels of aggregation (e.g. country, state, and city).

As mentioned above, the document-frequency-based measure of corruption has a correlation of $r = .62$ with Transparency International's corruption perception index. At the state level the document-frequency proxy is correlated $r = .59$ with (Edward L. Glaeser and Raven E. Saks, 2006)'s conviction-based corruption index, and $r = .44$ with (Richard T. Boylan and Cheryl X. Long, 2003)'s survey-based one.

Using the document-frequency proxies for corruption as the dependent variable we replicate the results of (Jakob Svensson, 2005) and (Edward L. Glaeser and Raven E. Saks, 2006) who establish the correlates of corruption at the country and state level respectively. Finally, we provide the first city-level index of corruption (for the United States).

Our research informs a growing literature from various disciplines that attempts to obtain quantitative information by conducting searches on large databases of documents. The majority of the existing research has concentrated on making inferences about the authors of the analyzed text; be it their beliefs (Werner Antweiler and Murray Z. Frank, 2004, Robert Tumarkin and Robert F. Whitelaw, 2001, Peter D. Wiysocki, 1998), preferences (David Godes and Dina Mayzlin, 2004, Yong Liu, 2006), sentiments (Feng

Li, 2006, Paul C. Tetlock, Forthcoming) or political bias (Matthew Gentzkow and Jesse M. Shapiro, 2006).

Two exceptions are (Edward L. Glaeser and Claudia Goldin, 2004), who *qualitatively* analyzed variation in the number of newspaper articles to discuss major changes in corruption in the United States during the 20^{th} century, and (Roland G. Jr. Fryer et al., 2005) who proxied for crack-cocaine availability through time.[3]

In relation to these literatures we make three notable contributions. First we demonstrate that analyses of document-frequencies need not be limited to making inferences about the authors of the written text or about the specific events described in the text, but more generally, to proxy for the relative frequency of any variable that can be expressed in frequencies. Second, we advance the conditions under which such proxying is likely to be valid, aiding future researchers in their decision on whether to use document-frequencies as proxies, and third, we validate empirically the use of document-frequency with several demonstrations.

The rest of the paper is organized as follows. Section 2 introduces the conceptual framework, section 3 contains the empirical analyses of the document-frequency based proxies for salient economic and demographic variables while section 4 those of corruption. Section 5 concludes.

2. Conceptual Framework

In this section we lay out a framework establishing the conditions under which document-frequency is likely to be a valid proxy for occurrence-frequency. We shall

[3] Fryer et al. also attempted to capture cross-sectional variation in crack availability but obtained null results. We believe this was the case because their document-frequency data violate two of the data requirements put forward in this paper (data checks #4 and #5).

refer to transformations (in a sense specified below) of the occurrence-frequency of phenomenon *p* in location *l* with $Y_{p,l}$ and to the corresponding transformations of the document-frequency obtained by querying a document database (e.g. the internet) with a set of keywords *k*, by $\hat{Y}_{p,l,k}$ (we utilize subscripts only when needed). We focus on a linear first-order approximation to characterize the relationship between *Y* and $\hat{Y}$:

$$(1) \qquad \hat{Y}_{p,l,k} = \alpha_{p,k} + \beta_{p,k} Y_{p,l} + \varepsilon_{p,l,k}$$

where $\alpha_{p,k}$ is a phenomenon-keyword specific intercept, $\beta_{p,k}$ corresponds to the impact of the occurrence of phenomenon *p*, on the number of documents written about it including keywords *k* , and $\varepsilon_{p,l,k}$ to the residual.

Equation (1) is useful for organizing our discussion of various data-checks that can be performed to assess conditions which make a high correlation between $\hat{Y}$ and *Y* more likely ex-ante. We list all these data-checks in Table 1.

Table 1

2.1 $\alpha_{p,k}$: Maintaining p and k constant.

The most intuitive problem that can arise when attempting to proxy for occurrence-frequency with document-frequency is α varying across queries; if α is not constant then β cannot be identified. This means that document-frequency is not useful for proxying for occurrence-frequency *across* phenomena.

Different phenomena elicit different levels of overall interest (variation in α from *p*) and, in addition, keywords relevant to different phenomena vary in how common it is for documents about such phenomena to utilize that specific keyword (variation from *k).*

As an example, suppose occurrence-frequency of cause of death by airplane and car crashes were to be approximated by the document-frequencies for the queries for "car crash" and "plane crash". Differences in such document-frequencies could be driven not only by differences in the occurrence-frequency of such accidents, but also by the idiosyncratic appeal to write about each of the two causes of death *and* by the percentage of all documents about automobile accidents containing the keywords "car crash" vis-à-vis the percentage of airplane accidents documents containing "plane crash." This problem is greatly reduced when comparisons are made across queries that maintain both p and k constant.

<u>Data check #1:</u> *do the different document queries maintain phenomenon and keywords constant?*

2.2 $\beta_{p,k}$: frequencies and our basic premise.

Our basic premise, that *ceteris paribus* the occurrence of a phenomenon increases the likelihood that a written document about it will be created, is equivalent to assuming that $\beta_{p,k}>0$. Two data checks can be used to assess the validity of this premise. The first is straightforward: the variable of interest must be expressed in terms of a relative frequency. The second is that the keyword chosen to search for documents about it is more likely to be employed following the occurrence than the non-occurrence of the phenomenon of interest.

The keyword "education" exemplifies violations of both requirements. First, "education" characterizes a term which does not have a frequency interpretation (unlike, say, "high-school dropouts"). Second, both an increase and a decrease in the quality of education in a given location may lead to more documents with the keyword "education."

The second requirement need not rely on subjective judgment alone. It can be assessed empirically by examining the content of the documents resulting from a given query. In particular, a researcher can sample the contents of a selection of the documents found through a particular query and assess whether keyword *k* is often utilized to demark the non-occurrence of *Y*.

<u>*Data check #2:*</u> *is the variable being proxied,* Y, *a frequency?*

<u>*Data check #3:*</u> *Inspect contents of documents found: is the keyword* k *employed predominately to discuss the occurrence rather than non-occurrence of phenomenon* p*?*

2.3 $\varepsilon_{p,l,k}$: Efficiency and bias.

$\varepsilon_{p,l,k}$ captures factors that influence $\hat{Y}_{p,l,k}$ other than $Y_{p,l}$. We will discuss here three such factors: sampling error, measurement error, and violation of the "redundancy-condition" for proxy variables

(i) Sampling error: Sampling error is reduced as sample size increases, of course, and hence, considering that document-frequency consists of the ratio of the number of documents matching the specific query over those about the location overall, sampling error will play a smaller role for topics and locations where the number of documents is "large." In section 3.4 we attempt to estimate what is "large enough" by obtaining correlations between document-frequency and occurrence-frequency for progressively larger samples of documents. Our results suggest that an average document-frequency as small as 50 can be enough to obtain reliable correlations with occurrence-frequency (see Figure 4).

Data check #4: is the average number of documents found large enough for variation to be driven by factors other than sampling error?

(ii) Measurement error and occurrence variability: for a given amount of measurement error specific to the relevant keyword and geographic level, a smaller variance in the occurrence-frequency of the phenomenon will lead to a higher noise-to-signal ratio and a smaller correlation between occurrence and document-frequency.

To exemplify this problem we proxied for cancer rates across US states and countries employing document-frequency of “cancer” in proximity to the name of the location of interest. We expected cancer rates to vary much more across countries than US states and hence for document-frequency to be a better proxy for the former. Data from the Center for Disease Control and GLOBOCAN confirmed both expectations. The coefficient of variation for cancer rates across states is .15 compared to .7 across countries, and hence the correlation between occurrence and document-frequency was much higher for variation across countries 0.34 ($p<.01$) than across states -.06 (n.s.).

Data check #5: is the expected variance in the occurrence-frequency of interest high enough to overcome the noise associated with document-frequency proxying?

(iii) Measurement error and polysemy: Another possible cause for large measurement error is that keywords often have multiple meanings, leading to false-positives; that is, to documents that do contain k but which are not actually about p. To mute this problem one should replace the keyword for a synonym with fewer other meanings (for instance using “African Americans” rather than “Blacks”).

Data check #6: Inspect content of documents found: does the chosen keyword have as its primary or only meaning the occurrence of the phenomenon of interest? [4]

(iii) Redundancy Condition: The final aspect of ε we discuss deals with its possible correlation with covariates of *Y*. This could be a problem if $\hat{Y}_{p,l,k}$ is estimated to learn about the relationship between $Y_{p,l}$ and other variables, X_l. A prerequisite for such use of proxy-variables is that Cov(X, $\hat{Y}$ |Y)=0 or equivalently that Cov(ε,X)=0 (Jeffrey M. Wooldrige, 2001). This condition means that, controlling for occurrence-frequency, document-frequency should be uncorrelated with the covariates of occurrence-frequency.

We consider two possible violations of this condition. The first occurs if *X* directly impacts $\hat{Y}$, independently of *Y*. As an example consider Y_l=*gun ownership* in city *l*, to be proxied via $\hat{Y}_{k,l}$ with *k*=”guns”, and a regression was then to be estimated with violent crime, *X*, as a dependent variable (i.e., X=OLS($\hat{Y}$)). If the tendency to write about guns increases not only as more guns are owned, but also as more guns are used (e.g. in violent crime), then the correlation between the two will be a biased estimate of the relationship between gun *availability* and crime, towards the relationship between gun *use* and crime,

[4] Fryer et al (2005) computed measures of crack-cocaine availability across cities based on newspaper stories containing the word “crack”, “cocaine” and the name of the city and found no cross-sectional correlation with their 4 other proxies, average correlation: .02 (we thank Roland Freyer for sharing their data). To explore the cause of this null result we conducted (proximity) searches utilizing these keywords and found that for most cities there simply were too few articles to make comparisons across them meaningful. For example, for the year on which most articles appeared, 1989, 45% of all cities had 10 or fewer documents. Variation across cities when the number of documents is so small is likely to be over-ridden by sampling error. We also hand checked the results for one city, Oakland, and found that 80% of the proximity searches were true-positives, compared to 33% of the regular searches, which is what Fryer et al employ. Their data, therefore, violated data-checks #4 and #6.

One way to diagnose this problem is to conduct queries that combine keywords for the occurrence of interest and its covariates (e.g. k=”*gun* AND *murder*”); the greater the share of documents that include the keyword for the covariate, the greater the potential bias.

If a problem is identified, *k* can be modified to reduce or eliminate it by, for example, employing keywords less likely to be used only in association with X. In the violent example these may include “gun shows” or “gun magazine” instead of simply “gun” or/and by explicitly requesting the search engine to exclude keywords associated with *X* (e.g., using Boolean search to query [(*guns NEAR Oakland) NOT murder NOT crime)*].[5] Comparisons of the results obtained when such corrections are and are not implemented should provide guidance of the extent to which Cov($\hat{Y}$,X|Y)≠0 is driving the results.

<u>*Data check #7:*</u> *Inspect content of documents found: does the chosen keyword also result in documents related to the covariates of the occurrence of interest?*

The second scenario under which the redundancy condition may be violated is the presence of an omitted variable, *Z*, which affects both *X* and $\hat{Y}$ independently of Y. For example, suppose that more cosmopolitan cities foster greater discussion of socioeconomic issues. Estimates of the correlation between a given covariate X, for instance average education, and the document-frequency of a given socioeconomic issue

[5] NEAR corresponds to a “proximity” search; NOT excludes pages including the specified words. Some illustrative results: the query for “*gun*” on January 19th, 2007 lead to 29.1 million hits on Exalead, of which 3.3 million, or 11%, also contain the words murder, murders or murdered. In contrast, of the 155,744 documents for “*gun show*” only 4,720, or 3%, contained such words.

like “poverty” ($\hat{Y}$) will be biased towards the relationship between average education and cosmopolitanism (Z). i.e. Cov($\hat{Y}$,X) will be biased towards Cov(Z, X).

To fix this problem additional searches can be conducted to proxy either for the underlying omitted variable (e.g. “cosmopolitan”) or for the suspected latent variable influenced by the omitted one (e.g. “socioeconomic”) and assess the impact of controlling for this additional document frequency on the parameter estimates of interest.

> <u>Data check #8:</u> *are there plausible omitted variables that may be correlated both with the document-frequency of the variable of interest and its covariates? If so, control for the omitted variable with an additional document-frequency proxy.*

3. Demonstrations with observable occurrence-frequencies

We begin the empirical analyses with a few demonstrations of how document-frequency can be used to proxy for occurrence-frequency. We conducted our document-frequency estimations both on the internet, using the search engine Exalead, [6] and on the local newspaper database *Newsbank.* [7] We focus on contemporaneous web searches and on newspapers published in the five years between 9/1/2001 and 31/8/2006, because the Newsbank's coverage is very limited before the initial date.

To conduct this initial demonstration we selected variables capturing salient socioeconomic dimensions and readily available at the state and city level. In particular, we constructed proxies for share of the population that is African-American, Hispanic, and foreign born, and for both murder and poverty rates.

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[6] At the time of our data-collection, only Exalead provided the option of conducting proximity searches, using 16-word textual distances

[7] We considered two other newspaper databases: *Lexis-Nexis* and *Factiva*. We chose *Newsbank* because it has the largest set of local newspapers and because, unlike *Lexis-Nexis*, it does not place a limit on the number of documents found on a single query. We queried both Newsbank and Exalead utilizing specially designed PERL scripts. Importantly, we added considerable time delays between queries to avoid imposing unreasonable burdens on the servers.

We obtained occurrence-frequency data for these variables from aggregate census counts, the FBI's Uniform Crime Reports, and HUD State of the Cities Database, respectively. For state level poverty we use the percentage of population with income below one half of the state median. For poverty at the city level we do not have microdata for all the cities so we use instead the official poverty rate as reported by the census. [8]

To estimate document-frequency we conducted proximity searches with the keywords "African American OR African Americans," "Hispanic OR Hispanics," "Immigrant OR Immigrants," "poverty," and "murder." We used all cities with a population of 100,000 or more in the 2000 census and all 50 states as locations. We excluded cities that have the same name as another city of more than 100,000 inhabitants, such as Arlington and Springfield.

As mentioned above, we calculate document-frequency as the ratio of documents obtained via a proximity search and the total number of documents with the name of the location. The distributions of both occurrence and document-frequencies tend to have a right skew, and we conduct all analyses on the log of these variables.[9] Figure 2 shows the occurrence and document-frequency distributions of the share of African-Americans across cities and their log-standardized version. The graphs also display the normal distribution that has the mean and variance corresponding to the data.

Figure 2

To assess the validity of this transformation we estimated the parameter λ in Box-Cox regressions of the general form:

[8] Note that these poverty rates are computed utilizing a nation-wide nominal income threshold, overestimating poverty in cheaper cities and underestimating it for expensive ones. This measurement error induces a conservative bias in our estimated correlations.

[9] We add 1 to the numerator so that the few cases with 0 documents can be included in the analyses..

$$(2) \qquad \frac{(\hat{Y}_{p,l,k})^{\lambda} - 1}{\lambda} = \alpha_{p,k} + \beta_{p,k} \frac{(Y_{p,l})^{\lambda} - 1}{\lambda} + \varepsilon_{p,l,k}$$

Where, again, $\hat{Y}_{k,p,l}$ is the relative document-frequency of occurrence *p* with regards to location *l* as proxied by keyword *k* and $Y_{p,l}$ is the corresponding occurrence-frequency. The estimate of λ indicates the optimal Box-Cox transformation to both variables. λ = 0 indicates a log transformation.

We fitted the Box-Cox model for our 5 keywords, both for the internet and newspapers, both at the city and state level. The average of the resulting 20 estimates of λ was *M* = -0.107, *SE* = 0.037. While this is statistically significantly different from zero it is quite close to it. Indeed, 12 of the 20 point estimates are not statistically different from 0. Furthermore, the log transformations are very highly correlated with those resulting from using the λs from the Box-Cox transformation,

3.1 Data checks

Before conducting the analyses we examine whether the variables of interest pass the data-checks put forward in our framework. They of course pass checks #1 (keywords are kept constant across locations), and # 2 (occurrence of the phenomena can be expressed in relative frequency terms).

For data-check #3 (keyword is more commonly used for occurrence rather than non-occurrence of phenomenon) and #6 (keyword's primary meaning is that of the phenomenon of interest) we conducted searches for each of the keywords in proximity to the word "city" and examined the contents of the first 50 documents found. For "African American" and "Immigrants" all 50 documents were true positives (e.g. *Cleveland's*

African American Museum and the *Coalition for Humane Immigrant Rights* in Los Angeles). For "Hispanics" and "Poverty" 49 out of 50 were true positives. For murder, in contrast, only 14 out 50 pages made direct allusion to actual murder cases or murder rates many documents referred to murder mystery clubs, TV shows, or pop songs. In the pool of 250 documents sampled, no document made allusion to any of the keywords to signify absence or reduced occurrence of the phenomena (e.g. "no immigrants" or "lack of poverty," "less Hispanics," or similar). Data-check #3 hence passes all keywords, while data-check #6 does too with the exception of *"murder."*

Data-check #4 requires raw document-frequency to be high enough that variation in relative frequencies across locations can have a reasonable signal to noise ratio. In our data, the average number of internet documents found for a given keyword ranged between 410 (for *"corruption"* at the city level) and 35,957 (for "*African Americans*" at the state level; both number are much higher than what our calibrations in section 3.4 suggest are sufficient for obtaining valid proxies.[10]

Data-check #5, requiring occurrence-frequency to experience substantial variation, will typically consist of a qualitative a-priori assessment. For the variables in this demonstration, however, we can directly assess the variation in occurrence-frequency since we are proxying for observable variables. In Table A2 in the Appendix we provide summary statistics for all the variables being proxied. The coefficients of variation are relatively high across the board, hovering around 75%-110%. Poverty is the notable exception, with a coefficient of variation of just 9% at the state level, for example. We should expect, therefore, that poverty's document-frequency will be less strongly

[10] See Table A1 in the appendix for a full list of the number of documents found for each keyword at different levels of analysis. For newspapers the range is between 97 for "corruption" at the city level and 3,085 for "murder" at the state level.

correlated with its occurrence-frequency. Finally, data-checks #7 and #8 do not apply here since we are not estimating regressions.

In sum, we expected positive correlations between occurrence and document-frequency for the social phenomena under consideration. The data-checks, however, suggest that we should encounter weaker correlations for murder with its high rate of false-positives, and for poverty with its low occurrence-frequency variation.

3.2 Results

To provide an intuitive sense of the relationship between document and occurrence-frequency for these variables, Figure 3 depicts quintile averages for each of them at the city level. The vertical axes contain the occurrence-frequency of the variable being proxied, and the plotted lines the average of occurrence-frequency by quintile of document-frequency in the left column and by quintile of occurrence-frequency in the right column. For example, the two plots in the first row show that in cities with the highest quintile of document-frequency about African Americans, 31 percent of the population is African American, compared to 48 percent for cities in the highest quintile of occurrence-frequency of African Americans. Overall, the document-frequency figures show increasing profiles, albeit they are flatter than those of the occurrence-frequency figures.

Figure 3

Table 2 shows the correlations between document-frequency and occurrence-frequency for the variables depicted in Figure 3 at both state and city level. All correlations are positive, with 28 out of the 30 being significant at the 5 percent level and 26 at the 1 percent level. Internet-based document-frequency is correlated on average

.439 with occurrence-frequency, almost identical to the correlation between newspaper-based document-frequency and occurrence-frequency, .440.[11]

Table 2

We interpret the positive correlations between document and occurrence-frequency as supportive of our contention that, for data that pass the multiple data-checks, greater occurrence-frequency of a specific phenomenon is associated with increased document-frequency of that same phenomenon.

Considering that the five variables we proxied are related to socio-economic status it is possible that rather than five independent demonstrations, the above correlations capture the *same* correlation between document-frequency and occurrence-frequency of low socioeconomic status, five times.

A more troubling concern is that this single correlation could be spurious. This could occur if people living in cities with greater frequency of low socioeconomic status were interested in writing about socioeconomic issues for reasons other than a high local occurrence-frequency per-se. For example, one may worry that large numbers of documents are written about African Americans in Philadelphia not because of Philadelphia's large African American community, but because of Philadelphia's large Democratic Party voter base, say, which will tend to discuss *all* socioeconomic issues, *including* those pertinent to the African American community.

We address these concerns in Table 3, where we report the cross-correlations of document-frequency and occurrence-frequency of African-Americans, with the occurrence-frequency of all five demographic variables used in the above

[11] Table 1 reports Pearson correlations. Unreported Spearman correlations (based on rank and therefore not sensitive to outliers or log-standardization) were very similar. The averages across all variables are .47 for Newspapers and .45 for the Internet.

demonstration.[12] Contrary to the null hypothesis that there is a single latent variable driving all correlations in Table 2, several of the cross-correlations between African American document-frequency and the occurrence-frequency of other variables are negative, and –importantly- similar to the cross-correlations in occurrence-frequency. For example, the cross-correlation between the occurrence-frequency of Hispanics and the document-frequency of African-Americans is -.40 across cities, compared to an actual correlation between both occurrence-frequencies of -.54.

Table 3

An alternative way to address this concern, suggested in the conceptual framework, consists of controlling the suspected omitted variable also with an additional document-frequency proxy. Importantly, this approach can easily be applied in situations where, unlike the present example, actual occurrence-frequencies are not observable.

If a single latent variable accounts for the multiple correlations we obtain, then partialing out the variance contained in a proxy of such a variable should substantially mute the (spurious) correlations. Because we are concerned with an overall tendency to discuss socioeconomic issues, we estimated the relative document-frequency of the keyword "socioeconomic." If the correlations from Table 2 arise because of a spurious association between the occurrence-frequency of those variables with the tendency to discuss socioeconomic issues, this variable should help us capture this trend and weaken the obtained correlations. Contrary to this prediction, we find that controlling for relative frequency of "socioeconomic" leaves the correlations between document-frequency and

[12] We focus on the African-American share because this is the variable for which document-frequency is more strongly correlated with occurrence-frequency and therefore where we have more power. Considering that we are seeking to show lack of correlation across variables this is the most conservative test we can take. We focus on states and major cities for analogous reasons.

occurrence-frequency from Table 2 largely unchanged: .41 on average for states, .38 for cities, and .44 for large cities, compared to .52, .38 and .42 respectively.

3.3 Monotonicity

We have established that document frequencies are strongly correlated with occurrence frequencies *on average*. Here we examine whether the relationship between the two is monotonic. This would not be the case if, for instance, at very high or low levels of occurrence *changes* in empirical frequencies were negatively related to *changes* in publication frequencies at the margin.

To examine this issue we pooled observations from all variables at the city level and estimated a spline regression. We identified cutoff points for quintiles of occurrence-frequency (of all variables pooled) and then each observation's occurrence-frequency was compared to these 'knots'.

In particular, let the new five spline variables be represented by S_i with *i*=1 to 5, and the inter-quintile cutoff point separating quintile *i* from quintile *i+1* be represented by k_i.

The value of S_i is determined by the following conditions:

If $y < k_i$ then $S_i = 0$

If $k_i \leq y \leq k_{i+1}$ then $S_i = y - k_i$

If $y > k_{i+1}$ then $S_i = k_{i+1} - k_i$

Note that $y = S_1+S_2+S_3+S_4+S_5$.

A regression with document-frequency as the dependent variable and S_1 through S_5 as predictors estimates the marginal impact of occurrence-frequency on document-frequency separately for variation in occurrence-frequency happening in each of its five quintiles.

Considering that we pooled observations across all phenomena we include slope dummy interactions for them (e.g., a "murder" dummy interacted by occurrence-frequency).[13] Table 4 shows the results for both internet and newspaper based document-frequencies. All point estimates are positive, and with a few exceptions significant, indicating that within each quintile of occurrence-frequency, a marginal increase in occurrence-frequency is associated with an increase in document-frequency in the margin.

Table 4

3.4 Reliability and sample size

As mentioned in our discussion of data check #4, if the absolute document-frequencies are small, variation across locations will be overridden by sampling error and hence the resulting proxy will be unreliable. In this subsection we gauge the relationship between sample size and the strength of the measured correlations

The ideal way to do so would be to query the full databases of documents we use (Newsbank® and Exalead®) and to create random subsamples of varying sizes from the resulting sets of documents. This approach, unfortunately, is prohibitively costly, as it requires *downloading* and analyzing the millions of documents that are obtained with the queries (e.g., just with "New York" there are over 60 million web documents).

As an alternative, we conducted queries on the full universe of documents but restricting searches so that only documents published during shorter periods of time

[13] Main effect dummies are not included because the variables were standardized separately. African-American share is the excluded interaction.

would be considered. We focus on newspaper data at the city level using Newsbank®. In particular, rather than conducting a single query per location-variable pair for all documents published between 2001 and 2006, we conducted 60 such queries per location-variable pair (e.g. "crime" NEAR "Los Angeles"), restricting the results to have been published during each of the 60 months.[14] The resulting document-frequencies are hence based, on average, on samples 1/60 the size of the original sample. By adding up partial sums for different (randomly selected) months we can then create larger samples.

We assess the impact of increasing average absolute number of documents by monitoring the evolution of the correlation between actual occurrence-frequency and document-frequencies computed over samples of increasingly larger sizes.[15]

Figure 4 shows the results from this exercise conducted on two different random subsets (without replacement) of 30 months each. The x-axis contains the average number of documents in the cumulative sample, as more and more months are added in random order, and the Y-axis the correlation of the proxy arising from that sample with the corresponding occurrence-frequency. Random sample 1 is plotted with dark points, whereas sample 2 is pictured using transparent diamond signs.

Figure 4

The results depicted in Figure 4 are highly comparable for the two random subsamples we employed (which have no overlap). They suggest that an average number of documents as low as 50 can generate valuable proxies for occurrence-frequency, and

[14] We conduct these searches only on Newsbank because internet searches with date restrictions, although possible, are not very reliable. Most notably, they obviously do not retrieve documents that were uploaded in the past but which are no longer available.

[15] The fact that we are sampling at the month level rather than independently at the document level reduces the efficiency of our samples. Truly random subsamples should converge faster, leading to an even smaller number of documents required to achieve a robust proxy.

that increasing average number of documents above 200 no longer noticeably increases accuracy.

4. Document-frequency based measures of corruption.

The results from the previous section demonstrated that document-frequency can be significantly correlated with occurrence-frequency. In this section we examine whether such correlation can be exploited to construct proxies for unobservable variables, which can then be used to learn about the covariates of the variable of interest.

We focus on corruption for two main reasons. First, doing so reduces possible concerns of data snooping to a minimum. Because published papers have studied correlates of corruption both at the state and country level, by concentrating on corruption we require the exact same technique to replicate prior findings in settings with independent sources of variation.

Second, the study of corruption characterizes the ideal application for the quantification of document-frequency: approximating the occurrence-frequency of a phenomenon that is otherwise very expensive to measure. Transparency International's Corruption Perceptions Index (CPI), the most commonly used international measure, averages information from 16 different surveys on experts and businessmen, some of them containing responses from more than 4,000 individuals. The high costs associated with data collection on corruption not only lead to large expenses, but also to censored, incomplete, or even nonexistent data sets. The International Crime Victim Survey from the year 2000, for example, which includes questions about bribes, was administered in only 48 countries. Quantifying document-frequency, in contrast, is virtually free and can in principle be conducted at any level of aggregation.

We present results using both internet and newspaper document-frequency, but center our discussion on the internet measures: these always work as well, if not better, than newspaper-based variables, are more widely available, and reflect documents from a much more diversified set of social agents.

4.1 Country-level variation

We start by analyzing corruption at the country level. We conducted searches for "corruption" in proximity to the name of 154 countries, deflating the resulting number of documents by the number obtained searching only the countries' names. The resulting correlation between occurrence and document frequencies is positive and significant: 0.62 (see figure 1 for a plot chart).

An important question is the extent to which the documents we are finding are actually discussing Transparency International's CPI. On the one hand that would be good news for the validity of the technique, as it would demonstrate its ability to capture relevant information. On the other it would be bad news if document-frequency works solely because it relies on existing occurrence-frequency estimates readily available online. We addressed this issue by conducting a new search adding a restriction that excluded all documents containing the word "*transparency*," presumably leaving out an important share of documents that discuss corruption in relation to the CPI.[16] If document-frequency was mostly picking up variation created by the CPI, then the new index should be much less closely correlated with the CPI. The new correlation, however, is virtually identical: .60.

[16] The queries were of the following general form: ((*corruption NEAR <country>*) *NOT transparency*)).

Replicating published results

Several papers have investigated the correlates of corruption across countries. In his review of the literature, Jakob Svensson (2005) estimated several regressions using various alternative measures of corruption as dependent variables, and as independent variables those hypothesized to predict corruption by various theories, making his paper an ideal benchmark.

Tables 2, 3 and 4 in his paper contain three specifications combining different correlates of corruption. We report our results for regressions using all those independent variables in our Table 5. The predictors are per-capita income in 1970, education level in 1970 (average number of years of schooling for people over 25), average (imports/GDP) between 2000-2004, and the number of days it takes to open a business in that country (we utilize the same sources cited by Svensson in his paper).

Because each variable has a different set of missing observations, we report both univariate regressions and a single multivariate one, with a much smaller sample size. Table 5 reports the regression results using as the dependent variable the log-standardized versions of TI's CPI index (first column), and our document-frequency based one (second column).

Table 5

In the four univariate regressions we obtain the same qualitative results with our document-frequency proxy and with the CPI (both in terms of sign and statistical significance). Furthermore, point estimates (recall that these are log standardized regressions) are quite close. The only exception is 'number of days it takes to open a business,’ where the document-frequency point estimate is less than half that obtained with Transparency International’s CPI.

The lower panel in Table 5 shows the results combining all four predictors into a single regression. Comparing both columns the general pattern is the same: document-frequency obtains results very similar to those obtained with the CPI, with the exception of the number of days to open a business. The results from Table 5 indicate that one can learn almost the same about the correlates of international corruption by either conducting expensive surveys of thousands of individuals or by running a few hundred searches on the internet, which takes a matter of hours.

4.2 State level variation

We next turn our attention to corruption across states in the United States. Unlike the case of corruption across countries, no widespread index of corruption exists for different states. We are aware of two assessments of state level corruption; we used both as benchmarks for our document-frequency based index of state corruption.

The first consists of a survey conducted by (Richard T. Boylan and Cheryl X. Long, 2003). They provided a questionnaire to 834 state house reporters, obtaining 293 responses (from 45 different states). They constructed their corruption index with the average of some of the questions in their questionnaire.

The second assessment of corruption across states is that of (Edward L. Glaeser and Raven E. Saks, 2006), referred to as *GS* for the remainder of the paper. They constructed a state-level corruption index based on the number of government officials convicted for corrupt practices through the (federal) Department of Justice (DOJ). In particular they divided the average number of DOJ corruption convictions over the 1976-2002 period by the state's average population during that same period.[17]

As *GS* acknowledge, there is a problem with deflating convictions by population, as doing so assumes that the number of government officials that could be corrupt has a linear relationship with population. States, of course, differ in the proportion of their citizens working for the government and hence at risk of engaging in the kind of behavior which could lead to a federal conviction. With this consideration in mind, and particularly because size of government is one of the predictors used by GS, we use in addition to the index published in their paper, one which deflates DOJ convictions by the average number of government employees during 1976-2002.[18]

Altogether we have 5 measures of corruption at the state level: (i) the original *GS* index, (ii) *GS* computed deflating by number of public employees rather than population for 1976-2002 (iii) Boylan and Long (2003)'s survey, (iv) internet based document-frequency index, and (v) newspaper based document-frequency index. In order to compare these variables measured in different units, as was done in the previous sections, we log-standardize all indexes.

Figure 5 depicts the relationship between measures (ii) and (iv). Corruption measured by average convictions per public employee during the 1976-2002 period appears in the vertical axis and document-frequency of corruption on the internet on the x-axis. The graph shows an obvious association between both measures of corruption.

[17] Corporate Crime Reporter, http://www.corporatecrimereporter.com/corruptreport.pdf, constructs essentially the same index.

[18] Glaser and Saks (2006) point out that their preferred deflator would have been the number of public officials by state, for which data are not available. Number of public employees, however, is available. We suspect it is more highly correlated with number of officials than state population is.

The correlations among all indexes are presented on Table 6. The average correlation between the internet measure and the three occurrence-frequency based measures is .49 (column 1). Interestingly, internet document-frequency is more highly correlated with the DOJ and survey-based indexes than they are with each other (although the difference is not significant at conventional levels).

***Table 6 ***

When convictions are divided by public employees rather than population, the correlations with other corruption measures increase (e.g. from .43 to .59 with internet document-frequency and from .31 to .41 with Boylan & Lang (2003)'s survey. This is consistent with our claim that number of public employees is a more appropriate denominator for corruption convictions.

We now move to replicating previous corruption research at the state level. We estimate regressions with our various corruption measures as dependent variables and the same predictors used in *GS* table 4, column 1, as independent variables: income inequality (Gini in 1970), median income (in 1970), education (share of population with college degree in 1970), share of employment provided by the government, (log of) population size, share of population living in an urban area, and regional dummies. This specification nests all previous ones in GS.[19]

The results are reported in our Table 7. Column 1 uses the original *GS* measure, column 2 the alternative version deflated by number of public employees, column 3 an

[19] Most of the data for the predictors used in the regressions for Table 7 were kindly provided by Raven Saks.

internet based document-frequency index, column 4 the survey and column 5 the newspaper based document-frequency.[20]

***Table 7 ***

Comparing columns 1 and 2, we see that deflating convictions by number of public employees rather than population increases the size of most coefficients, maintaining significance mostly unchanged (consistent with the notion that such deflator reduces measurement error). The notable exception is, not surprisingly, the estimated impact of share of government employees, which drops to less than 5 percent of its original size and is no longer significant.

Most importantly, column 3 shows that, using our internet document-frequency measure of corruption as an independent variable, we obtain results that are largely consistent with those from columns 2 and 1. Greater income inequality, greater income levels and lower education are all associated with an increase in the internet corruption index in this specification. The point estimates are of similar magnitudes across the three columns, although education is slightly less important in the document-frequency regression. The biggest difference across columns occurs with the impact of share of

[20] In Table 5 we exclude from the analyses the state of Georgia, because (contrary to our data-check 6) most documents allude to the Caucasian country and not to the US state of interest: for example, 34 out of the 50 first pages containing the keyword “corruption” and “Georgia” allude to the ex-Soviet Union country. We also exclude Washington State, since a majority of web pages alluding to Washington are actually in relation to the District of Columbia. 28 out of the 50 first pages containing the keyword “corruption” and “Washington State” allude to the US capital: if included in the sample Washington State would be a huge outlier, with internet frequencies two and a half standard deviations above the mean and occurrence-frequencies two standard deviations below the mean. While becoming slightly more imprecise, our main results are actually robust to the inclusion of these two states: the coefficients (standard errors in parentheses) on inequality, income, and percentage with bachelors degree become 0.68 (.28), 0.62 (.27), and -0.31 (.16)

employment provided by the government. It is estimated as small positive and non-significant in column 2 and *negative* and significant in column 3.[21]

The results obtained with the survey of house state reporters, column 4, are not dissimilar qualitatively, but many of the parameter estimates are not significantly different from zero. Our internet document-frequency-based proxy, hence, appears to be a *better* measure of corruption, in this case, than costly survey data.

Throughout their paper, *GS* show numerous others regressions studying the relationship between corruption and a variety of additional variables, controlling for all variables included in Table 7 except income inequality. In our Table 8 we report the results from replicating the subset of these additional regressions which *GS* find to have a significant relationship with corruption (at the 5% level). Some of the estimates using the log version of GS's measure are no longer significant, but point estimates for the occurrence-frequency and document-frequency based measures of corruption are remarkably similar.

***Table 8 ***

In sum, we construct a measure of corruption which is both highly correlated with the two existing measures of state level corruption, and which we use to replicate the findings from existing research assessing the correlates of corruption at the state level.

4.3 City- level variation

We now turn to using document-frequencies to produce the first assessment of corruption at the city level in the US. Document-frequency-based proxies have an

[21] To assess whether we capture variation in corruption in addition to that which is captured by the predictors employed by GS, we estimated a regression equivalent to Column 2 in Table 5 adding internet document-frequency as a predictor. We obtained a positive and significant point estimate (t-stat = 2.66).

important component of error. Considering that previous research has shown that readers of rankings tend to overweight positional differences over differences in the underlying continuous variables that are used to construct these rankings (Devin G. Pope, 2006), we present the results from our estimation of corruption at the city level in groups of 10 cities. The results for the 61 cities with more than 250,000 inhabitants are presented in Table 9. The top-10 cities are consistent with our priors on corruption, including San Diego, New Orleans, Los Angeles, Philadelphia, and Chicago. Conversely, among the bottom-10 we find cities seldom used as examples of corrupt local governments.[22]

***Table 9 ***

To complement this subjective assessment of the city-corruption index, we also estimated regressions employing it as a dependent variable. Unfortunately, we are unable to exactly replicate the state-level or country-level specifications because some covariates at greater level of aggregation are either unavailable for cities (e.g. income inequality) or lack variation (e.g. percentage of the population living in cities). In order to obtain a benchmark from existing measures of corruption, therefore, we estimate a new state-level regression with the same covariates employed for the city-level regressions.

The results are presented on Table 10. In all columns except 2 & 3 the dependent variable is city-level corruption as proxied by internet document-frequency. In column 2 it is city-level corruption as proxied by Newspaper document-frequency and in column 3 state level corruption as measured by DOJ corruption convictions per public employee.

Table 10

[22] In line with data check #6, we dropped cities whose names are more often used to mean something other than the city in question. In particular we dropped Independence, Washington, Toledo, and Athens. "Toledo," for instance, is much more commonly used to refer to the former Peruvian president than to the city in connection to corruption. For example, in January of 2007, of the first 10 hits for "Corruption NEAR Toledo" in Exalead, nine discussed the former president and only one the Ohioan city.

The results across columns 1,2 and 3, i.e. for variation across cities and sates, are similar in qualitative terms, lending credence to the city level corruption measures we have created. In particular, city and state level regressions indicate that locations with greater income, smaller populations, and fewer minorities and immigrants have less corruption. The main difference in point estimates is the South dummy, which is positive at the state level (indicating greater state corruption in the South than in the omitted region, the west) but is negative in the city level regression.

One of the benefits of obtaining city level data is the possibility of studying covariates that vary at a finer level of aggregation than at the state level. As an example we examine if industrial cities tend to experience more corruption (possibly as a consequence of their recent economic downturn). To this end we add as a predictor of city-level corruption the share of employment in the manufacturing sector, which proves –surprisingly- negatively associated with corruption (see column 4).

We next examine two possible concerns regarding our city-level analyses of corruption. The first is the possibility that variation in our corruption proxy is driven not by variation in the occurrence-frequency of corruption across different cities, but rather, by variation in the tendency to write about social issues in relation to different cities. For example, we find that larger cities (in population) tend to be measured as more corrupt, the concern is that this correlation may result from people being more inclined to writing about social issues with regards to larger cities.

As suggested in our discussion of such problem in data-check #8, we assess the potential importance of this concern by estimating the document-frequency of a variable that may proxy for the omitted variable in question. We use again the document-frequency of the keyword “socioeconomic” and add this variable as a control in column 5. Although it proves a significant predictor of the document-frequency of corruption, the point estimates for the other variables remain largely unchanged, suggesting omitted variables of the kind we considered are not a problem in the original specification.

The second concern we address is the possibility that our city-level regression results capitalize on state-level variation in corruption. To address this concern in column 6 we control for our state-level document-frequency based measure of corruption. We find that (i) state-level document-frequency of corruption is not a significant predictor of city-level corruption (controlling for city observables), and (ii) that more importantly, its introduction in the model does not greatly influence the point estimates of the other independent variables.[23] This strongly suggests we are capturing variation in corruption above and beyond state-level corruption.

In sum, our document-frequency measure of corruption at the city level both generates a ranking of cities that is consistent with our preconceptions and with findings about the covariates of corruption at greater levels of aggregation.

6. Conclusions

We hypothesized that, *ceteris paribus*, the occurrence of a social phenomenon increases the chances people will publish content about it. In this paper we have demonstrated that using variation in relative measures of internet and newspaper document-frequency in reference to a phenomenon can capture cross-sectional variation of the underlying corresponding empirical occurrence-frequencies.

[23] Results are almost identical if, as in Table 5, we exclude Georgia from the regression (3 cities).

We begun by introducing a framework that specified the circumstances under which the frequency of documents containing specific keywords in relation to a given location (e.g. a country, state, or city) might be used as a proxy for the occurrence-frequency of the discussed social phenomenon. We then validated the technique showing strong, positive, statistically significant correlations between document-frequency and empirical data on several major demographic variables.

Focusing on the measurement of corruption at the country, state and city level we also found that document-frequency based measures of corruption were highly correlated with published measures of corruption. Regression analyses utilizing the document-frequency based measures of corruption for countries and states replicated the sign, significance and magnitude of the covariates of corruption from published papers. Strikingly, using data that we obtained from the internet and newspaper databases in a matter of hours, we obtain results similar to those arising from data based on expensive surveys or administrative collection processes, illustrating the simplicity and potential power of this approach.

Our results demonstrate that when the requirements put forward in the framework are met, document-frequency's correlation with occurrence-frequency allows researchers to construct proxies for otherwise unobservable variables. This opens the door to studying previously not-measured variables, as we do here with city-level corruption. A promising application is the possibility of creating proxies for suspected omitted variables in settings where the dependent variable *is* observable, an exciting possibility considering that a large number non-experimental field studies suffer from potential bias due to omitted variables.

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Figure 1: Corruption in the World

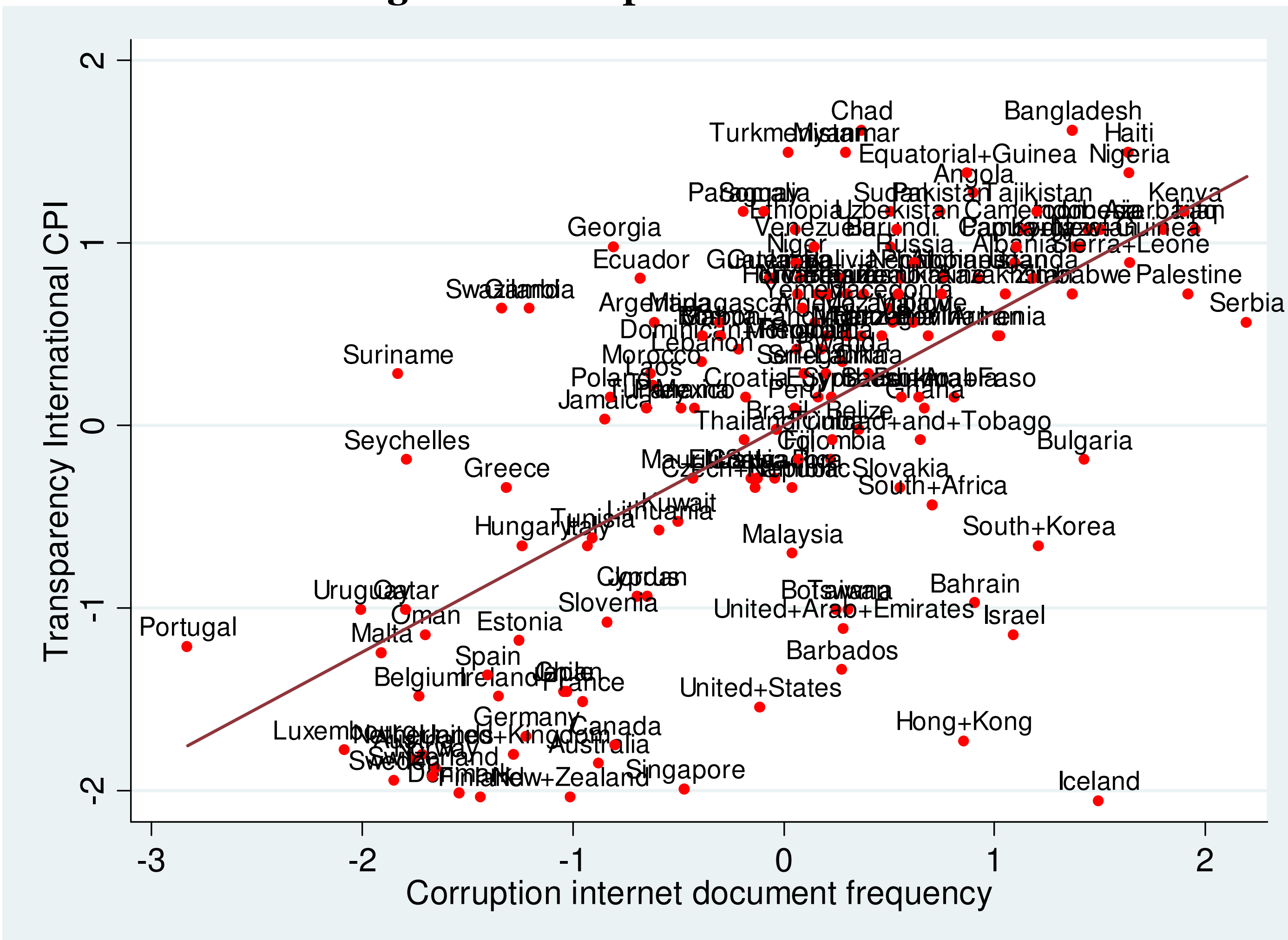


Figure 2: Log-standardizing the Data Sources – African Americans in US Cities

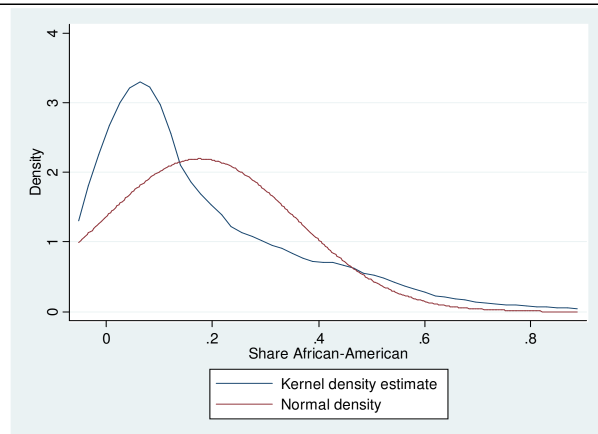
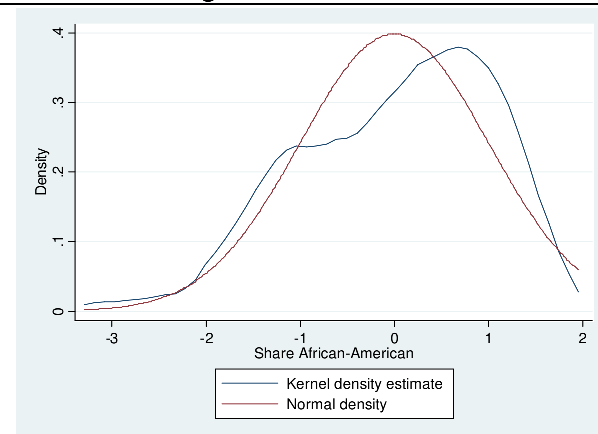
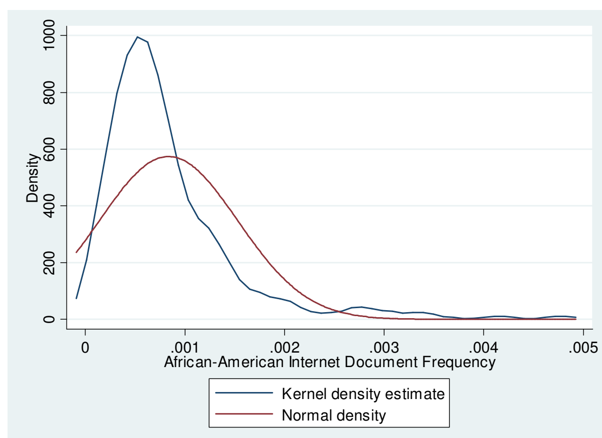
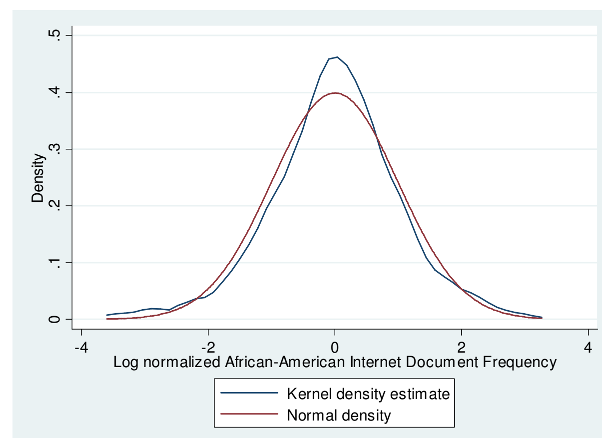
	Raw Data	Log Standardized Data
Empirical Occurrence Frequency		
Internet Document Frequency		

Figure 3: Average Data by Frequency Quintiles (cities)

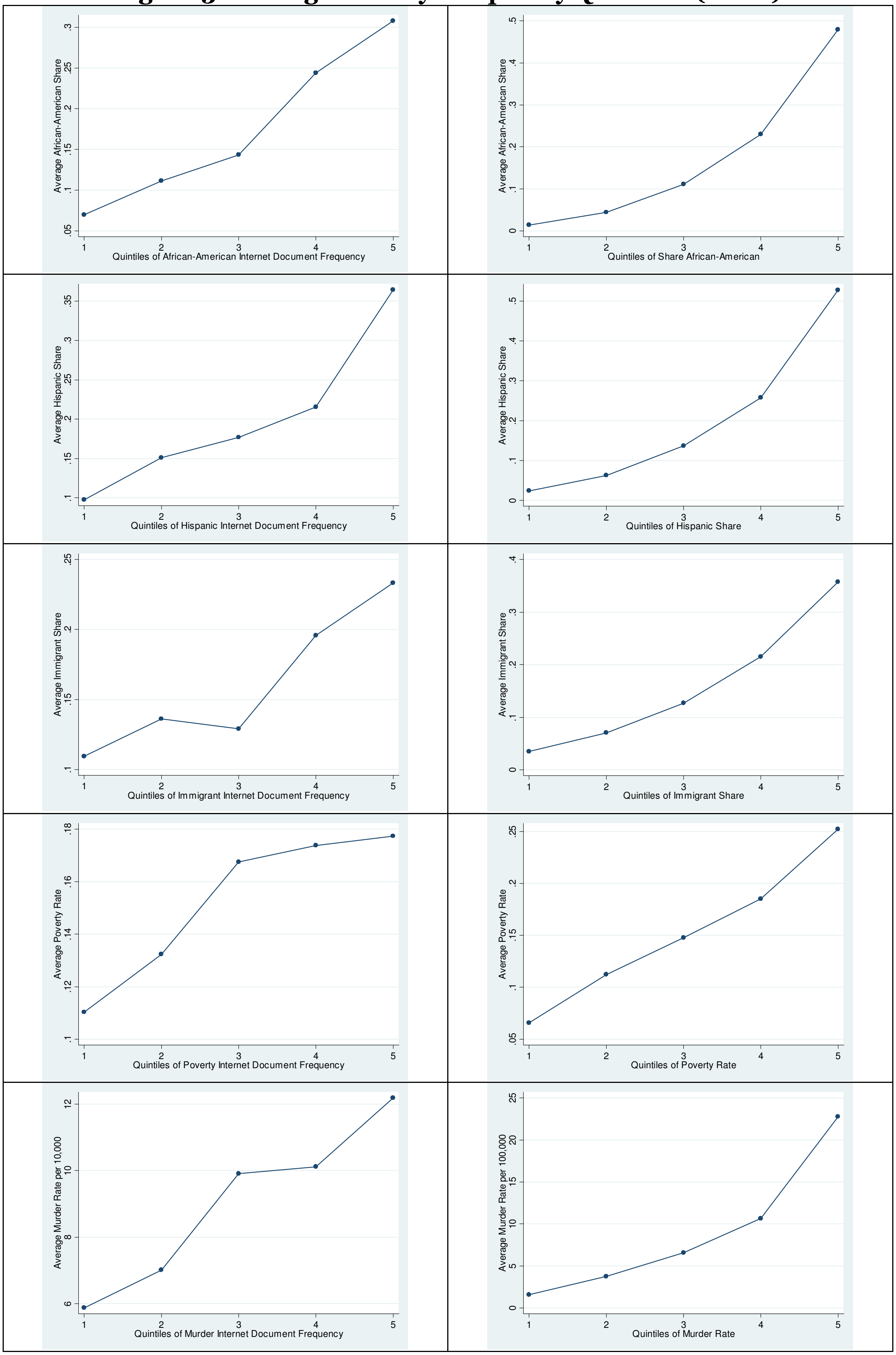
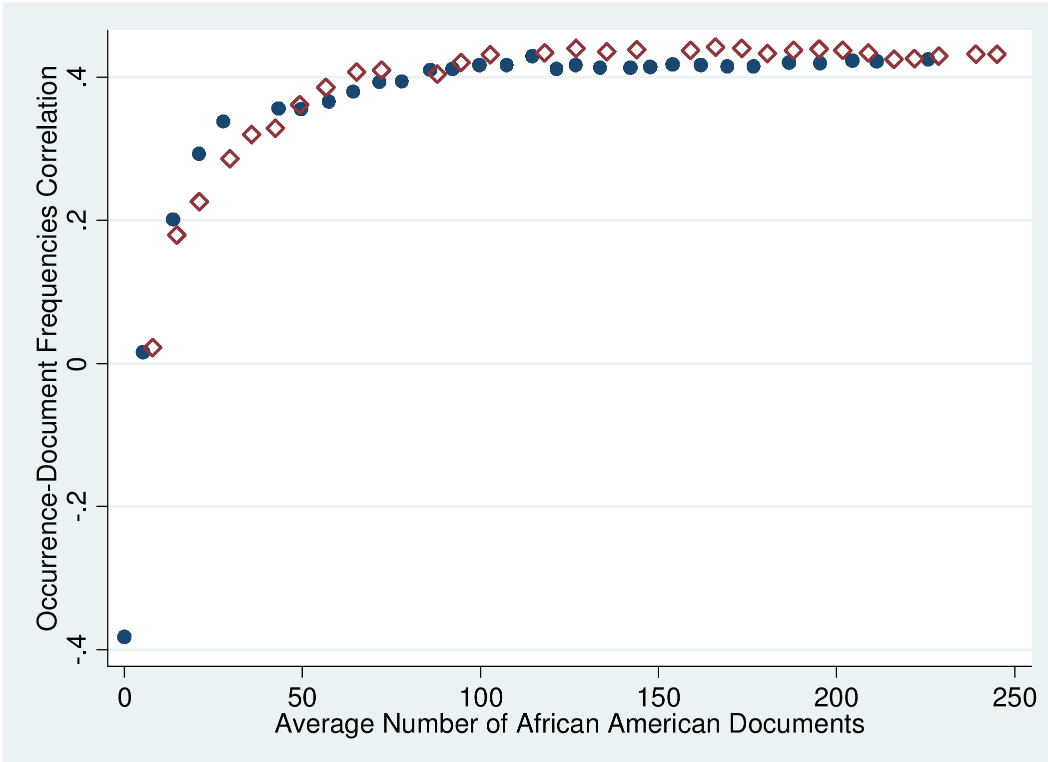


Figure 4
Correlations by Sample Size across Alternative Samples



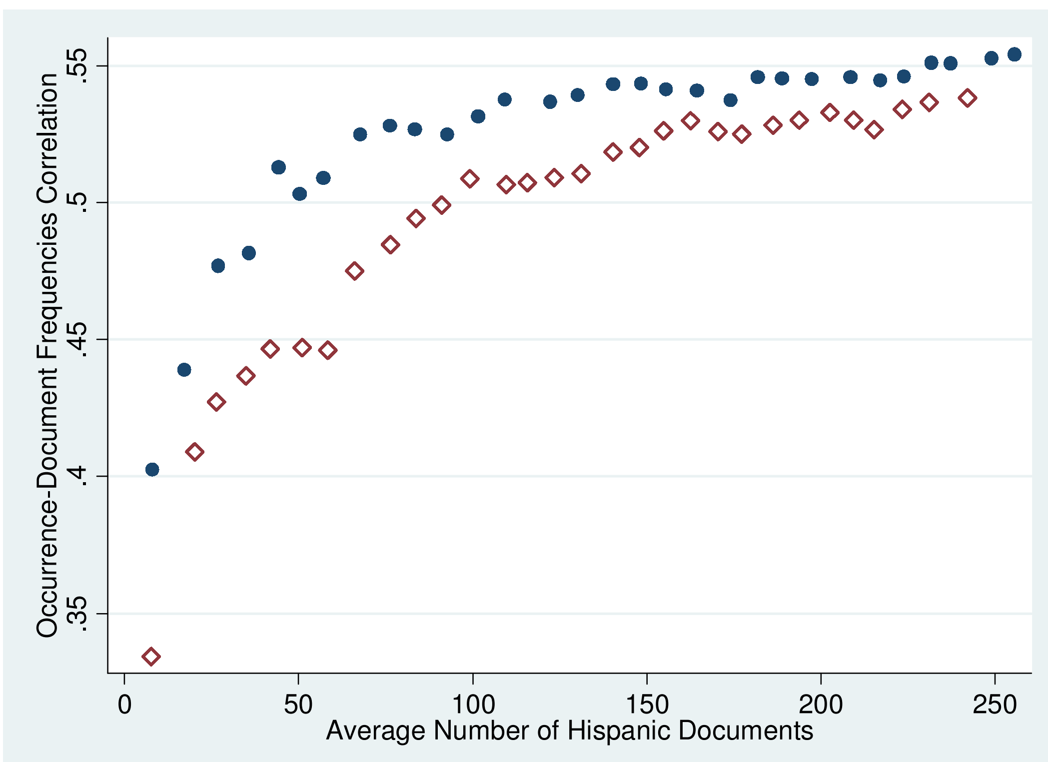
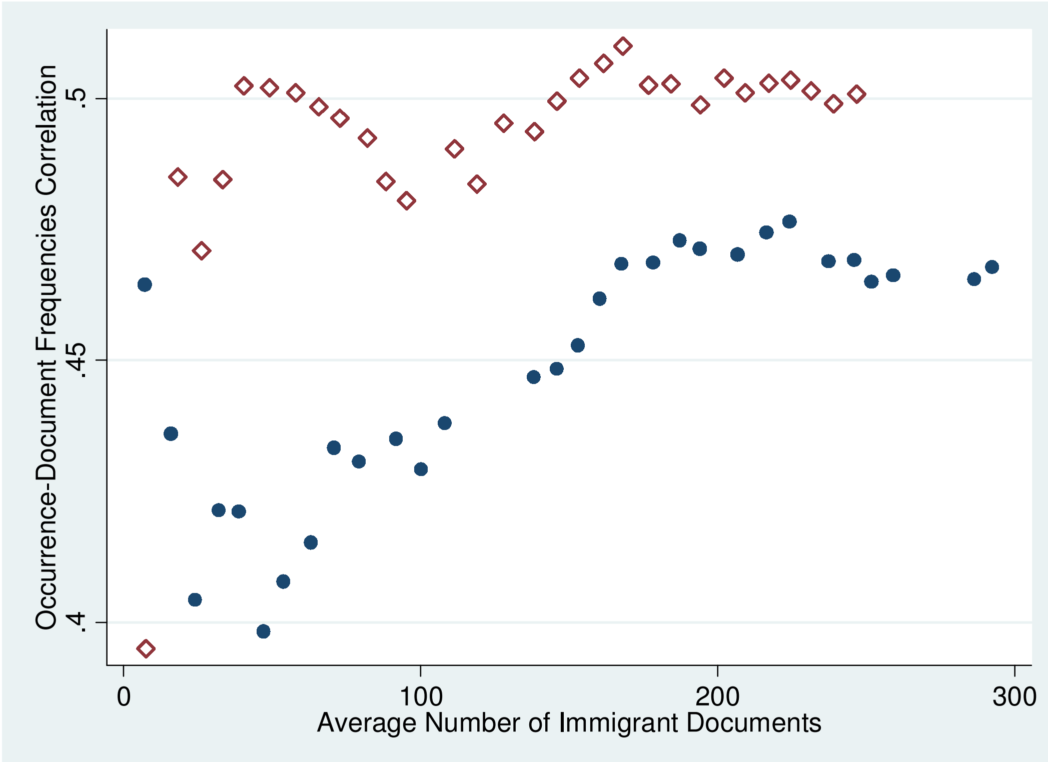


Figure 4 (Continued)



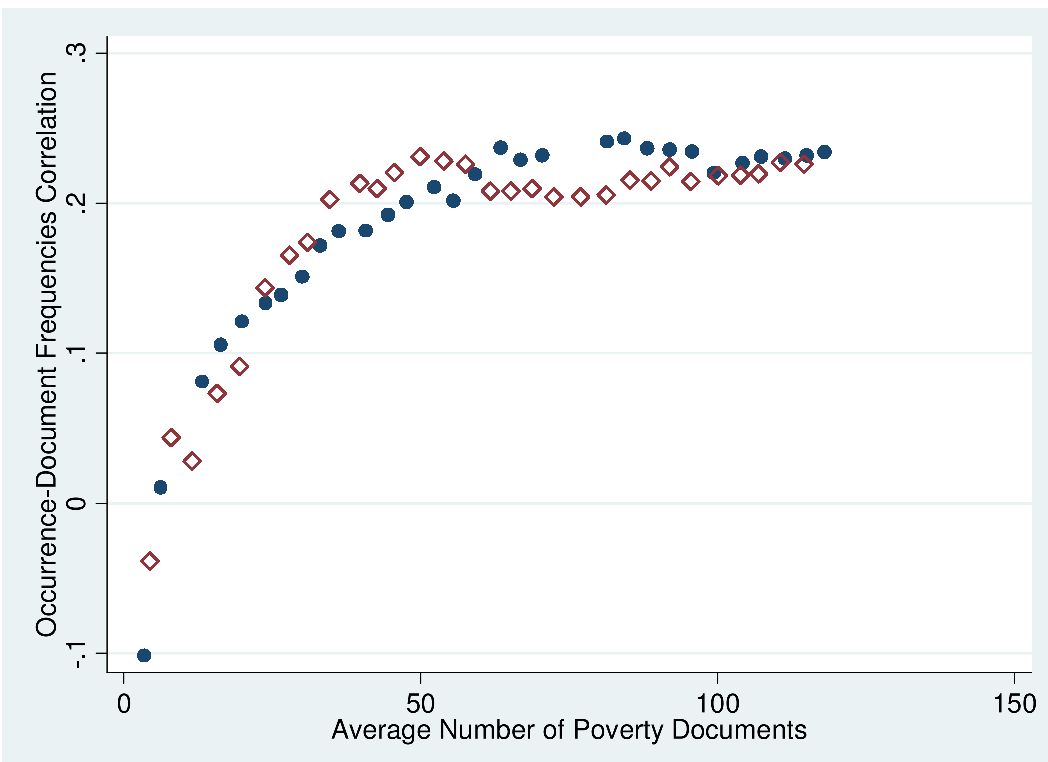


Figure 4 (Continued)

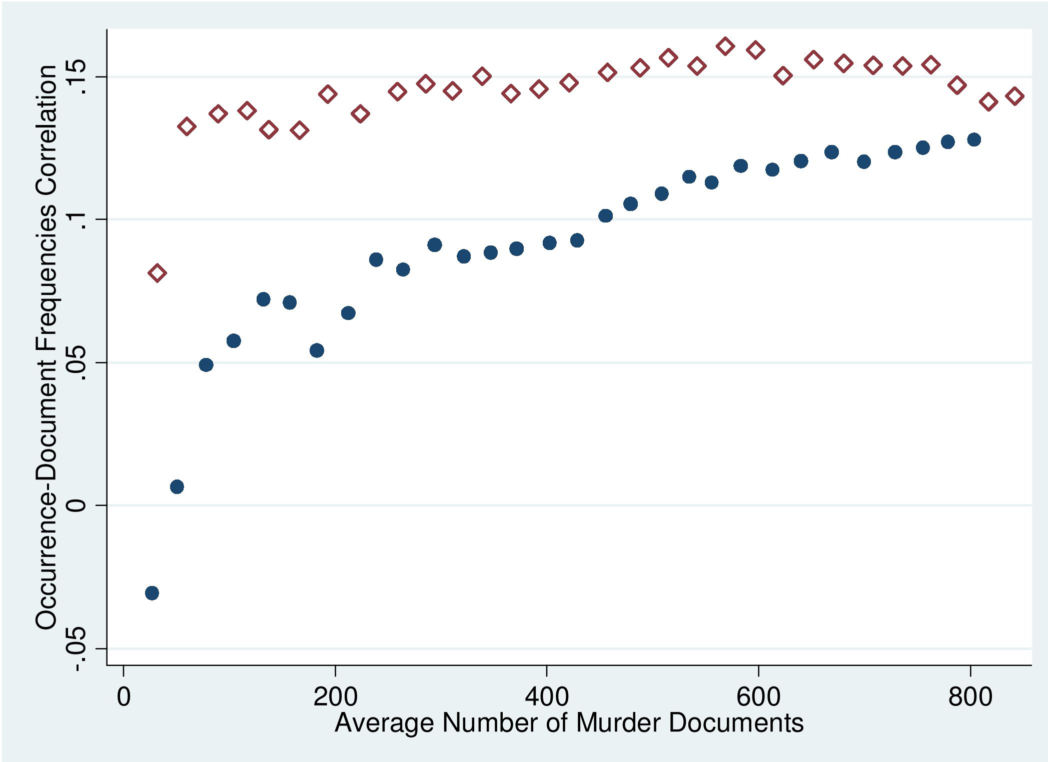


Figure 5: Corruption in the USA

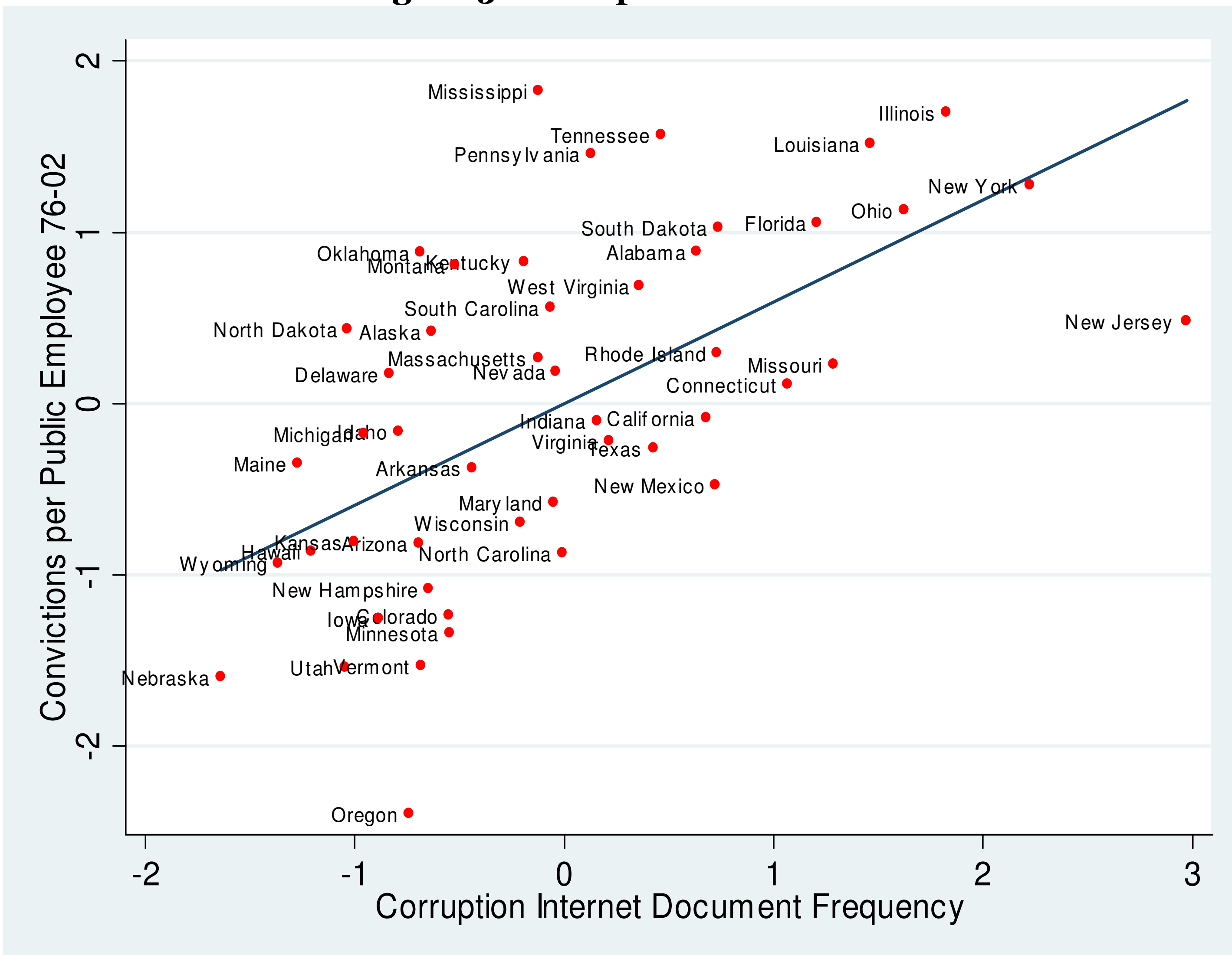


TABLE 1

Summary of Data-Checks From Framework

	Element in equation 1	Data-check
1	$\alpha_{p,k}$	Do the queries maintain phenomenon and its keyword constant?
2	$\beta_{p,k}$	Is the variable being proxied expressed as a frequency?
3	$\beta_{p,k}$	Inspect contents of documents found: is the keyword *k* employed predominately to discuss the occurrence rather than non-occurrence of phenomenon p?
4	$\varepsilon_{p,l,k}$ *(Sampling error)*	Is the average number of documents found large enough for variation to be driven by factors other than sampling error? (section 3.3. suggests larger than 50 can be large enough)
5	$\varepsilon_{p,l,k}$ *(Sampling error)*	Is the expected variance in the occurrence-frequency of interest high nough to overcome the noise associated with document-frequency proxying?
6	$\varepsilon_{p,l,k}$ *(Measurement error)*	Inspect content of documents found: does the chosen keyword have as its primary or only meaning the occurrence of the phenomenon of interest?
7	$\varepsilon_{p,l,k}$ *(Measurement error)*	Inspect content of documents found: does the chosen keyword also result in documents related to the covariates of the occurrence of interest?
8	$\varepsilon_{p,l,k}$ *(Redundany Condition)*	Are there plausible omitted variables that may be correlated both with the document-frequency of the variable of interest and its covariates? If so, control for the omitted variable with an additional document-frequency proxy

Notes: Data-checks arise from discussion of framework in Section 2.

TABLE 2

Correlations Between Occurrence and Document Frequencies

	Internet			***Local Newspapers***		
	US States	Cities		US States	Cities	
		pop>100k	pop>250k		pop>100k	pop>250k
African-Americans[a]	0.70	0.43	0.67	0.82	0.50	0.61
Hispanics[a]	0.50	0.43	0.43	0.74	0.48	0.56
Immigrants[a]	0.51	0.37	0.44	0.69	0.40	0.46
Poverty rate[b]	0.41	0.34	0.31	0.37	0.26	0.20[†]
Murder rate[c]	0.48	0.29	0.26	0.36	0.13	0.02[†]
Average	***.519***	***.375***	***.422***	***.596***	***.354***	***.371***
N	50	227	62	50	227	62

Notes: Entries in table are correlations between the occurrence and document-frequency for each variable described in the first column. Internet document frequencies are obtained with the search engine Exalead® while Newspaper frequencies with Newsbank®. Correlations are significant at the 5% level unless stated otherwise.

[†] Not significant at 5%

[a] As percentage of the overall population reported 2000 US Census

[b] Poverty rate is the percentage of households below half the median of state income measures.

[c] Murder rate is the average murder rate per 10,000 in 2000-2005 according to the FBI's Uniform Crime Reports.

TABLE 3

Cross Correlations of Frequency of African-Americans with Other Frequencies

(1)	(2)	(3)	(4)
	Frequency of African Americans		
	Occurrence-Frequency	*Document-Frequency*	
		Internet	Newspapers
Occurrence-Frequency (States)			
African-Americans	1.00	0.70	0.82
Hispanics	0.16†	-0.08†	-0.05†
Immigrants	0.21†	-0.02†	0.06†
Poverty rate	0.21	0.47	0.36
Murder rate	0.80	0.62	0.65
Occurrence-Frequency (Cities population>250,000)			
African-Americans	1.00	0.67	0.61
Hispanics	-0.54	-0.40	-0.37
Immigrants	-0.48	-0.35	-0.31
Poverty rate	0.48	0.34	0.38
Murder rate	0.79	0.59	0.51

Notes: Each row in table reports the correlations between the occurrence-frequency of the variable listed in column (1), with frequency of African Americans. All correlations are statistically significant at the 5% level unless otherwise indicated.

† Not significant at 5%

TABLE 4

Spline Regressions Assessing if Relationship Between Occurrence-Frequency and Document-Frequency is Monotonic

	Dependent Variable	
	Internet document-frequency	Newspaper document-frequency
Predictors		
Spline 1	0.361***	0.428***
	(0.121)	*(0.120)*
Spline 2	0.287	0.573***
	(0.181)	*(0.180)*
Spline 3	0.668***	0.584***
	(0.220)	*(0.219)*
Spline 4	0.116	0.135
	(0.246)	*(0.245)*
Spline 5	1.027***	0.958***
	(0.203)	*(0.202)*
Socioeconomic Variable Dummies (K = 5)	yes	yes
Observations (City [226] * Socieconomic Variable [5])	1,130	1,130
R^2	0.13	0.12

Notes: Entries in table are point estimates from OLS regressions that pool all city-level observations for frequencies of African Americans, Hispanics, Immigrants, and Poverty and Murder rate. Robust standard errors in parenthesis below parameter estimates. The dependent variable is the log-standardized document-frequency. The five predictors are splines for the corresponding occurrence-frequency. These splines measure the distance between a given observation's occurrence-frequency and each of the 5 cutoff points between quintiles of occurrence-frequency,bounded by 0 from below and by the next quintile from above (see text for details). The reported point estimates assess the impact of changes in occurrence-frequency, within each of its five quintiles, on document-frequency. All five point estimates for the splines being positive indicates that higher occurrence-frequency is associated with higher document-frequency within each of the 5 quintiles of occurrence-frequency.

TABLE 5

Replication of Regressions Establishing Correlates of Country Level Corruption in (Svensson 2005), Tables 2, 3 and 4

	(1)	('2)	(3)	
Dependent variable is corruption as measured by:	Transparency International's *Corruption Perception Index*	Internet Based Document Frequency *(Exalead)*	Newspaper Based Document Frequency *(NewsBank)*	N
	Only education in 1970 as a predictor			
Log(Average education [in years] 1970, adults 25+)	-0.679***	-0.527***	-0.446***	*96*
	(0.100)	*(0.106)*	*(0.093)*	
	Only GPD per capita in 1970 as a predictor			
Log (real GDP in 1970)	-0.761***	-0.618***	-0.483***	*105*
	(0.060)	*(0.074)*	*(0.089)*	
	Only Imports/GDP as a predictor			
Log (average[imports/GDP] 1980-2004)	-0.081	-.0903	-0.196**	*145*
	(0.083)	*(0.072)*	*(0.079)*	
	Only days required to open a new business as a predictor			
Log (days to open new business)	.601***	.265***	.341***	*84*
	(0.055)	*(0.070)*	*(0.110)*	
	All four predictors			
Log(Average education [in years] 1970, adults 25+)	0.072	0.180	0.167	
	(0.096)	(0.167)	(0.137)	
Log (real GDP in 1970)	-0.747***	-0.889***	-0.611***	
	(0.139)	(0.167)	(0.159)	*54*
Log (average[imports/GDP] 2000-2004)	-0.181**	-0.205**	-0.316**	
	(0.075)	(0.078)	(0.120)	
Log (days to open new business)	0.271***	-0.050	0.215	
	(0.075)	(0.091)	(0.130)	

Notes: Entries in table are point estimates from log-standardized regressions. Robust standard errors below parenthesis. Horizontal lines separate regressions employing different subsets of predictors, sample sizes vary due to missing observations. Columns separate regressions employing different dependent variables. Document-frequencies are the ratios of documents found with the keyword "corruption" and the name of the country over the number of all documents found with the name of the country. Specifications replicate those published in Svensson (2005). See text for data sources.

* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE 6

Correlations of State Level Corruption Measures

	Document Frequency		Corruption Convictions[a]		Survey[d]
	Internet	*Newspapers*	*per inhabitant*[b]	*per public employee*[c]	
Document Frequency					
Internet	1				
Newspapers	0.75	1			
Corruption Convictions[a]					
per inhabitant[b]	0.43	0.45	1		
per public employee[c]	0.59	0.60	0.90	1	
Survey[d]	0.44	0.51	0.31	0.41	1

[a] Convictions correspond to Federal Department of Justice convictions on corruption charges of state officials (as used in Glaeser & Sak, 2006)

[b] Division of total number of convictions by population, original Glaeser & Sak (2006) indicator.

[c] Division of total number of convictions by number of public employees (authors' calculations).

[d] Survey of State House Reporters, Boylan & Lang (2003)

TABLE 7

Replication of Regressions Establishing Correlates of State Level Corruption in Glaeser and Saks (2006): Table 4 (1)

	(1)	(2)	(3)	(4)	(5)
Dependent Variable: Corruption as measured by	Convictions[a] per Inhabitant (76-02)	Convictions per Public[c] Employee (76-02)	Document Frequency *Internet*	Survey [d]	Document Frequency *Newspapers*
Income Inequality	0.786***	0.811***	0.927***	0.344	0.795***
	(0.168)	*(0.172)*	*(0.220)*	*(0.361)*	*(0.226)*
Ln(Income)	0.652***	0.759***	0.788***	0.599	1.050***
	(0.174)	*(0.192)*	*(0.231)*	*(0.403)*	*(0.235)*
Share of population in state with 4+ Years of College	-0.655***	-0.835***	-0.468***	-0.642**	-0.521***
	(0.152)	*(0.156)*	*(0.156)*	*(0.243)*	*(0.168)*
Share of all employees employed by the state government	0.386**	0.015	-0.401***	-0.052	-0.359**
	(0.173)	*(0.172)*	*(0.127)*	*(0.233)*	*(0.147)*
Ln(Population)	-0.009	-0.02	0.088	-0.199	-0.137
	(0.166)	*(0.178)*	*(0.121)*	*(0.175)*	*(0.117)*
Share of population living in urban environment	0.153	0.255	0.334***	0.660***	0.263*
	(0.188)	*(0.184)*	*(0.118)*	*(0.145)*	*(0.154)*
Census Region Dummies					
South	0.109	0.008	-0.523*	0.661	0.029
	(0.479)	*(0.478)*	*(0.309)*	*(0.427)*	*(0.302)*
Northeast	0.55	0.472	0.015	0.039	0.552
	(0.479)	*(0.466)*	*(0.335)*	*(0.449)*	*(0.343)*
Midwest	-0.003	-0.234	-0.55	-0.616	-0.544
	(0.521)	*(0.534)*	*(0.335)*	*(0.388)*	*(0.373)*
Observations	48	48	48	45	48
R^2	0.54	0.52	0.56	0.5	0.49

Notes: Entries in table are point estimates from log-standardized regressions. Robust standard errors below parenthesis. Columns contain regressions employing different dependent variables. Document-frequencies are the ratios of documents found with the keyword "corruption" and the name of the state over the number of all documents found with the name of that state. Regressions exclude Washington State and Georgia (see text)

* significant at 10%; ** significant at 5%; *** significant at 1%

[a] Convictions correspond to Federal Department of Justice convictions on corruption charges of state officials (as used in Glaeser & Sak, 2006)

[b] per *inhabitant* corresponds to dividing the number of convictions by the population of the state.

[c] per *public employee* corresponds to dividing the number of convictions by number of public employees the state.

[d] From (Boylan and Lang, 2003)

TABLE 8

Corruption Regressions with Additional Predictors Significant at the 5% Level in (Glaeser and Sak, 2006)

Dependent Variable: Corruption as measured by	Convictions per Inhabitant 76-02	Convictions per Public Employee 76-02	Internet Document Frequency	Newspaper Document Frequency
Racial Dissimilarity	0.402**	0.343	0.288	0.346*
	(0.169)	*(0.209)*	*(0.206)*	*(0.204)*
Share Black	0.381***	0.371**	0.317*	0.367
	(0.132)	*(0.155)*	*(0.183)*	*(0.221)*
Local Share of Gov. Employment	1.112	2.012	1.793	1.306
	(-1.368)	*(1.483)*	*(2.102)*	*(1.831)*
Integrity ranking, 2002	-0.025***	-0.026***	-0.015*	-0.019*
	(0.007)	*(0.008)*	*(0.008)*	*(0.011)*

Notes:

Entries in table are point estimates from log-standardized regressions. Robust standard errors in parentheses. Variables in table are those found by (Glaeser-Saks, 2006) to be significant at the 5% level in tables other than their Table 4 (which we replicate in our Table 7). These regressions also control for 1970 income, education, population, share government employment, urban share, and regional dummies. Regressions exclude Washington State and Georgia (see text).

TABLE 9

Document-frequency Based Corruption Measure at the City Level (pop>250,000). Sorted in Groups of 10 from Most to Least Corrupt, Alphabetical Within Group

Group	City Name	Group	City Name
1	Chicago	4	Austin
1	Las Vegas	4	Corpus Christi
1	Los Angeles	4	Fort Worth
1	Miami	4	Honolulu
1	New Orleans	4	Houston
1	New York	4	Long Beach
1	Philadelphia	4	Milwaukee
1	San Diego	4	Sacramento
1	San Jose	4	Santa Ana
1	St. Louis	4	St. Paul
2	Atlanta	5	Anchorage
2	Boston	5	Buffalo
2	Cleveland	5	Cincinnati
2	Detroit	5	Minneapolis
2	El Paso	5	Pittsburgh
2	Newark	5	Portland
2	Oklahoma City	5	Raleigh
2	Phoenix	5	Tampa
2	Riverside	5	Tucson
2	San Francisco	5	Wichita
3	Baltimore	6	Albuquerque
3	Dallas	6	Anaheim
3	Denver	6	Charlotte
3	Fresno	6	Colorado Springs
3	Lexington-Fayette	6	Indianapolis
3	Memphis	6	Jacksonville
3	Oakland	6	Louisville
3	San Antonio	6	Mesa
3	Seattle	6	Nashville-Davidson
3	Virginia Beach	6	Omaha
		6	Tulsa

TABLE 10

OLS Identifying Correlates of City Level Corruption

	(1)	(2)	(3)	(4)	(5)	(6)
Independent variable: Corruption as measured by	City Level Internet Document Frequency	City Level Newspaper Document Frequency	*State* Level (Convictions per public employee)	City Level Internet Document Frequency	City Level Internet Document Frequency	City Level Internet Document Frequency
Log of Income	-0.167**	-0.231***	-0.226	-0.154*	-0.156**	-0.157**
	(0.077)	*(0.078)*	*(0.171)*	*(0.079)*	*(0.070)*	*(0.071)*
Share Workers in Public Administration	0.021	0.069	0.192	-0.022	-0.044	-0.043
	(0.053)	*(0.050)*	*(0.180)*	*(0.056)*	*(0.054)*	*(0.055)*
Log of Population	0.232***	0.134**	0.083	0.201***	0.182***	0.183***
	(0.050)	*(0.054)*	*(0.229)*	*(0.054)*	*(0.050)*	*(0.050)*
Share African-American	0.135*	0.089	0.381**	0.163**	0.113	0.098
	(0.073)	*(0.074)*	*(0.171)*	*(0.075)*	*(0.068)*	*(0.074)*
Share Foreign Born	0.163*	0.187**	2.31	0.222**	0.181**	0.177**
	(0.083)	*(0.076)*	*(4.209)*	*(0.097)*	*(0.086)*	*(0.086)*
South	-0.401**	-0.113	0.53	-0.435**	-0.331**	-0.369**
	(0.170)	*(0.165)*	*(0.546)*	*(0.173)*	*(0.164)*	*(0.176)*
Northeast	0.345	0.527*	1.113**	0.267	0.266	0.176
	(0.231)	*(0.287)*	*(0.510)*	*(0.275)*	*(0.267)*	*(0.297)*
Midwest	-0.043	-0.169	0.684	-0.058	0.057	-0.01
	(0.206)	*(0.167)*	*(0.597)*	*(0.262)*	*(0.270)*	*(0.280)*
Share Workers in Manufacturing				-0.144*	-0.149*	-0.147*
				(0.083)	*(0.080)*	*(0.079)*
"Socioeconomic" Document Frequency					0.306***	0.310***
					(0.060)	*(0.061)*
State-Level "Corruption" Document Frequency						0.063
						(0.084)
Observations	224	224	50	224	224	224
R-squared	0.2	0.19	0.3	0.21	0.3	0.3

Notes: Entries in table are point estimates from log-standardized OLS regressions with corruption as the dependent variable. Robust standard errors below point estimates. Corruption in column 3 corresponds to the ratio of DOJ corruption convictions to the number of public employees in the respective state. The dependent variable in all other columns is the document-frequency of corruption at the city level. Column 5 adds the document-frequency of "Socioeconomic" to the specification from column 1 to control for idyosincratic differences in the tendency to discuss socioeconomic issues across cities. Column 6 adds document-frequency of corruption at the State level to account for state level variation in corruption.
* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix TABLE A1

Number of Documents: Averages and Standard Deviations

Panel A: The Internet

Documents with City Name and Keyword:	States			Large Cities			Small Cities		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
African-American	50	35,957	48,777	62	20,721	30,555	165	3,827	6,108
Hispanic	50	16,864	20,351	62	9,010	12,214	165	1,383	1,904
Immigrant	50	10,715	15,707	62	6,913	14,020	165	1,123	2,099
Poverty	50	5,265	5,355	62	3,027	6,710	165	877	1,983
Murder	50	13,043	13,764	62	10,495	21,454	165	2,558	4,695
Corruption	50	2,801	4,471	62	1,763	4,079	165	410	1,109
Total	50	32,100,000	24,600,000	62	18,000,000	17,500,000	165	7,315,665	18,700,000

Panel B: Local Newspapers (DataBank)

Documents with City Name and Keyword:	States			Large Cities			Small Cities		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
African-American	50	1,079	1,046	62	1,013	1,142	165	278	472
Hispanic	50	1,472	2,046	62	1,079	1,198	165	282	420
Immigrant	50	1,710	2,580	62	1,271	1,743	165	264	427
Poverty	50	691	551	62	476	540	165	145	287
Murder	50	3,085	2,927	62	3,054	3,241	165	1,119	1,485
Corruption	50	403	568	62	334	529	165	94	236
Total	50	817,391	705,792	62	705,126	599,778	165	226,077	251,421

Appendix TABLE A2

Occurrence Frequencies: Averages and Standard Deviations

Population Percent	States				Large Cities				Small Cities			
	N	Mean	Std. Dev.	σ/μ Ratio	N	Mean	Std. Dev.	σ/μ Ratio	N	Mean	Std. Dev.	σ/μ Ratio
African-American	50	10.33	9.70	0.94	62	22.36	18.87	0.84	165	15.61	17.33	1.11
Hispanic	50	8.81	9.44	1.07	62	20.47	19.16	0.94	165	19.89	20.36	1.02
Immigrant	50	7.71	5.85	0.76	62	16.10	12.50	0.78	165	16.01	12.51	0.78
Poverty	50	20.76	1.88	0.09	62	17.41	5.64	0.32	165	14.39	6.76	0.47
Murder Rate*	50	4.66	2.46	0.53	62	13.07	9.82	0.75	165	7.45	8.04	1.08
Corruption Rate**	50	3.13	1.48	0.47	62	NA	NA	NA	165	NA	NA	NA

* Murders per 10,000

** Convictions per 100,000 employees